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Machine learning for occupant-behavior-sensitive cooling energy consumption prediction in office buildings

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ABSTRACT

Building energy consumption prediction plays a key role in energy-efficiency decision making. With the advancement in data analytics, a number of machine learning-based building energy consumption prediction models have been developed in recent years. However, existing prediction models do not sufficiently take occupant behavior into account. Towards addressing this gap, this paper presents a machine-learning approach for predicting building energy consumption in an occupant-behavior-sensitive manner. In this approach, a model learns from a large set of energy-use cases that were modelled and simulated in EnergyPlus. The machine-learning prediction model was trained using a large dataset that includes 3-month hourly data for 5760 energy-use cases representing different combinations of building characteristics, outdoor weather conditions, and occupant behaviors. In developing the model, four machine-learning algorithms were tested and compared in terms of their prediction accuracy and computational efficiency: classification and regression trees (CART), ensemble bagging trees (EBT), artificial neural networks (ANN), and deep neural networks (DNN). The simulation results demonstrated the high impact of the variables considered in this study. For example, the highest energy-consuming case consumed over 3432 times more energy than the lowest-consuming case. Occupant behavior made a difference up to over 7 times in energy consumption. The DNN model with four hidden layers achieved 2.97% coefficient of variation (CV). Such high performance shows the potential of the proposed approach. The approach could help better understand the impact of occupant behavior on building energy consumption and identify opportunities for behavioral energy-saving measures.

1. Introduction

The building sector is the highest energy consumer in the world. For example, in the United States, 74.6% of the electricity, 27.2% of the natural gas, and 39.6% of all the primary energy are consumed by commercial and residential buildings [1]. A significant portion of this energy is consumed by the air conditioning, space heating, and water heating systems of the buildings to provide comfortable, productive, and healthy environments for the building occupants [2]. For example, these systems represent 17%, 15%, and 14% of the residential electricity consumption in the United States, respectively [3]. In the future, the energy consumed by buildings, especially the cooling and heating energy, is expected to further increase due to the more often occurrence of heat waves and cold spells caused by global-warming-related changes in the climate [4].

Building energy consumption prediction plays a key role in reducing the consumption [5]. The ability to predict the consumption is essential to increasing the efficiency of the electricity grid [6], as well as to evaluating the impact of different energy-saving measures at the building level. Building energy consumption prediction is, however, a difficult task, because building energy performance is affected by many interrelated physical, operational, and behavioral factors such as building material, occupancy schedule, and occupant behavior [7]. Machine-learning techniques are shown to be useful for many prediction problems due to their high accuracy and ease of use [8]. A significant number of research efforts have, thus, used machine-learning techniques to predict energy consumption and analyze the impacts of energy-saving measures such as energy-retrofit strategies and renewable energy technologies [9]. However, existing ML-based models, despite their importance, do not sufficiently take occupant behavior into account. They either do not consider occupant behavior at all or they only consider it in a limited way such as taking building operation schedules and/or

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occupancy into account [6].

Occupant behavior is not only one of the most significant factors that affect building energy consumption, it is also one of the main contributors to the uncertainty in the prediction results [10,11]. For example, Clevenger et al. [12] showed that occupant behavior can impact annual energy consumption in the order of magnitude of 75% for residential buildings and 150% for commercial buildings. Ioannou and Itard [13] showed that the effects of occupant-behavior factors are much more dominant on heating energy consumption, compared to building factors. Wang and Greenberg [14] investigated the impacts of window operation and showed that mixed-mode ventilation can result in 17–47% HVAC energy savings during the summer for various climates. Sun and Hong [15] showed that five occupant-behavior measures – including lighting, plug loads, comfort criteria, HVAC control, and window control – can achieve up to 22.9% energy savings individually and up to 41.0% if combined.

Towards addressing this research gap, this paper presents a study on taking a machine-learning approach to predicting building energy consumption in an occupant-behavior-sensitive manner. In this approach, the machine-learning models were trained using a dataset generated by EnergyPlus simulations. The simulations were conducted in a way to model a relatively large set of building characteristics and outdoor weather conditions, as well as emulate different occupant behaviors. A number of machine-learning algorithms were also tested and compared in terms of their prediction accuracy and computational efficiency.

2. Related works and research gaps

A significant number of recent studies have focused on building energy consumption prediction. These studies can be categorized along two dimensions: factors used for prediction and machine-learning techniques used for model development. Despite the importance of these studies, three primary research gaps are identified. Along the first dimension, there is a lack of approaches taking occupant behavior into account. Along the second dimension, there is a lack of studies focusing on deep learning and ensemble approaches.

2.1. Features used for machine learning

Existing machine learning-based building energy consumption prediction efforts have used many features that affect the consumption, such as outdoor weather conditions (e.g., dry-bulb temperature, solar radiation), indoor environmental conditions (e.g., room temperature, room relative humidity), building characteristics (e.g., geometry, orientation), time [e.g., type of day (e.g., weekday, weekend, holiday), type of hour (e.g., daytime, nighttime)], operation characteristics (e.g., building use schedule, number of occupants). For example, Dong et al. [16] predicted building energy consumption using mean outdoor dry-bulb temperature, relative humidity, and global solar radiation. Hong et al. [17] predicted annual heating and electrical energy consumption using 23 building and climate-related features. Ascione et al. [18] predicted energy consumption for space heating and cooling using 9 geometry, 30 envelope, 6 building operation, and 3 HVAC-related features. Zhang et al. [19] predicted hot water energy rate using only dry-bulb temperature. Rastogi et al. [20] predicted heating loads using window-to-floor ratio (WFR), window-to-wall ratio (WWR), form factor (volume/wall area), annual sum of internal heat gain, and average sunlit percentage of envelope and predicted cooling loads using median dry-bulb temperature, inter-quartile range of dew-point temperature, WFR, and WWR. Paudel et al. [21] predicted heating demand using outside temperature, solar radiation, day type, occupancy profiles, operational power-level characteristics, and time-dependent attributes of operational power-level characteristics. Deb et al. [22] predicted diurnal cooling load using only previous loads. Jain et al. [23] predicted electrical consumption using previous electrical consumption values, temperature, day type, sine of the current hour, and cosine of the current hour. Platon et al. [24] predicted electricity consumption using outdoor air temperature, relative humidity, indoor air temperature, and some HVAC-related variables. Yu et al. [25] classified building energy use intensity (EUI) levels using climatic conditions (e.g., annual average air temperature), building characteristics (e.g., house type, construction type), household characteristics (e.g., number of occupants), and household appliance energy sources (e.g., space heating source, hot water supply source).

These studies were able to predict building energy consumption within acceptable accuracy ranges and provided important contributions to the field. However, despite their importance, none of them focused on taking the impact of occupant behavior into account. In developing machine learning-based prediction models, it is important to take the behavior of the building occupants into account, because it is one of the major factors that affect the energy consumption of the building and is one of the most significant contributors to the uncertainty in the prediction of this consumption [10,11].

2.2. Deep learning approaches

Deep learning approaches have been proven to outperform other machine-learning algorithms in many fields [26]. In the area of building energy consumption prediction, a significant number of studies have used artificial neural networks (ANN) with shallower architectures (i.e., ANN with a single hidden layer). For example, Li et al. [27] proposed a hybrid improved Particle Swarm Optimization algorithm (iPSO) – ANN model to predict hourly building electricity consumption, in which the iPSO algorithm was applied to adjust the weights and threshold values of the ANN structure. An et al. [28] proposed a multi-output feedforward neural network (FFNN)-based approach, which combines FFNN with empirical mode decomposition (EMD)-based signal filtering and seasonal adjustment, to predict the electricity demand of a week in 30-min intervals. Ekici and Aksoy [29] proposed an ANN-based model to predict annual heating energy consumption. ANN with deeper architectures, deep neural networks (DNN) [i.e., ANN with more than a single hidden layer], on the other hand, are less explored in the field of building energy consumption prediction. DNN was used in only a few studies such as Fan et al. [2]. Additional studies are, thus, needed to better understand the applicability and limitations of DNN in the building energy consumption domain – for example to understand how the number of hidden layers and the sizes of the datasets impact prediction accuracy and computational efficiency.

2.3. Ensemble approaches

Ensemble models consist of a number of models and are therefore likely to provide more accurate predictions than single models due to their stability [5]. A few studies have utilized ensemble techniques in the area of building energy consumption prediction. For example, Wang et al. [5] developed an ensemble bagging tree (EBT) model to predict the electricity demand of an institutional building. Wang et al. [30] developed a random forest (RF) model for hourly building energy consumption prediction. Tsanas and Xifara [31] developed an RF model to predict cooling and heating loads of residential buildings. Lahouar and Slama [32] proposed an RF model for short-term load forecasting. Jovanovic et al. [33] compared the performance of three ANN models – including FFNN, radial basis function network (RBFN), and adaptive neuro-fuzzy interference system (ANFIS) – to the ensemble of these three models and showed that the ensemble model achieved the most accurate prediction results. Such studies successfully applied ensemble techniques to building energy consumption prediction problems and showed that ensemble models can achieve more accurate predictions. More studies are needed to better understand the applicability and limitations of ensemble models in this domain (e.g., understand how the size of the training dataset affects prediction accuracy and computational efficiency), and their relative performance in comparison to deep learning algorithms such as DNN.

3. Methodology

The proposed occupant-behavior-sensitive energy consumption prediction approach included five primary steps: (1) modeling a set of buildings with different sizes and occupant behaviors, (2) conducting energy simulations in several locations using EnergyPlus, (3) pre-processing the simulation-generated data, (4) developing a set of machine learning-based prediction models that learn from these data, and (5) evaluating the performance of the developed models. EnergyPlus was selected to conduct the building energy simulations due to its capability to simulate a building close to its real situation [34].

3.1. Building and occupant-behavior modeling

A total of 1152 buildings were modelled to represent different occupant behaviors and building sizes. Other building characteristics, such as envelope thermal properties, were held constant to reduce the number of variables and therefore the simulation time. These properties were determined according to the industry standards (e.g., ASHRAE Standard 189.1–2017 [35]).

To capture the impact of different occupant behaviors on consumption, a set of cases that represent different behaviors were modelled. To model these cases, a set of five proxy variables that could represent behavior differences were identified and modelled in a parametric way: cooling setpoint, window status, lighting power density, occupancy density, and electric equipment power density. Three cooling setpoint cases, within the temperature range recommended by the ASHRAE Standard 55–2017 [36], were considered. For each of the lighting power, occupancy, and electric equipment power densities, two densities were considered: ±10% of the density for open offices in the ASHRAE Standard 189.1–2017 [35]. Two window operation cases were considered: non-operable windows and open during working hours. The natural ventilation rate through the windows was assumed as 5 air changes per hour. The window-operation strategies were adopted from Refs. [14,37]. The building operational characteristics (e.g., cooling setpoint) were determined as per the ASHRAE Standard 189.1–2017 [35]. Table 1 summarizes the variables and their values.

To create a dataset that represents different office buildings in the U.S., different building sizes were modelled. The geometric properties of the buildings were determined based on the categories given in the 2012 Commercial Buildings Energy Consumption Survey (CBECS) [38]. For the building floor areas, a value from each size category was used: 232 m^2 (2500 ft^2), 697 m^2 (7500 ft^2), 1858 m^2 (20,000 ft^2), 3716 m^2 (40,000 ft^2), 7432 m^2 (80,000 ft^2), 11,613 m^2 (125,000 ft^2), 23,226 m^2 (250,000 ft^2), and 46,451 m^2 (500,000 ft^2). For the number of floors, the most common three categories were considered: one-, two-, and three-story.

For the other building characteristics, the envelope thermal properties (e.g., wall and slab materials) were determined based on the ASHRAE Standard 189.1–2017 [35]. As such, the floor-to-floor height of the buildings was 3.66 m (12 ft). The perimeter zones of the buildings had operable windows for natural ventilation and cooling, and the window-to-wall ratio of each external surface of the buildings was 36%. The buildings were equipped with two packaged rooftop units, which use direct expansion (DX) cooling coils to supply cooling, with a rated cooling coefficient of performance (COP) of 3. The perimeter and core zones of the buildings had individual packaged rooftop units for cooling. The entire spaces of the buildings were designed as an open office. Table 2 shows the detailed envelope thermal properties of the buildings.

Table 1
Occupant-behavior variables.

Variable	Values
Cooling setpoint (occupied)	{22.8 °C, 24 °C, 25.2 °C}
Lighting power density	{9.59 W/m^2, 11.72 W/m^2}
Occupancy density	{0.05 $people/m^2$, 0.07 $people/m^2$}
Electric equipment power density	{6.88 W/m^2, 8.41 W/m^2}
Window operation	{Not operable, Open during working hours}

For implementation, the different occupant-behavior cases were simulated using the direct input approach due to its straightforwardness and accuracy [39]. The building geometries were modelled in SketchUp Make 2017. The operational characteristics, envelope thermal properties, and HVAC systems of the buildings were defined in OpenStudio 2.4.0. The combinations of 8 building floor areas, 3 numbers of floors, 3 cooling setpoints, 2 lighting power densities, 2 electric equipment power densities, 2 occupancy densities, and 2 window-operation strategies resulted in a total of 1152 cases. Due to the repetitive nature of modeling such a relatively large number of cases, a model producer script was written to create the EnergyPlus input files that represent the 1152 cases.

3.2. Energy simulations

The 1152 building models were simulated in EnergyPlus. The models were simulated in five cities, which represent five different climate zones in the United Sates, resulting in a total of 5760 model instances. According to the ASHRAE Standard 169–2020 [40], the United States has eight climate thermal zones, including very hot, hot, warm, mixed, cool, cold, very cold, and sub-arctic. However, because this study focuses only on cooling energy consumption, the cold, very cold, and sub-arctic climate thermal zones were not considered, and the cities were selected from the remaining zones. Table 3 shows the selected cities and their climate properties. The simulations were conducted from June 1 to August 31, with hourly time steps, resulting in a total of 2208 h. The typical meteorological year 3 (TMY3) weather data of the five locations were used. Prior to the energy simulations, the HVAC system of each model was autosized by EnergyPlus based on the corresponding city's summer design days. In order to have an undisturbed consumption pattern throughout the simulation period, the holiday schedules in EnergyPlus were removed. The simulations were conducted on a four-core personal computer, in parallel on all 4 cores, using EnergyPlus 8.8.0.

3.3. Data preprocessing

The EnergyPlus data were preprocessed in preparation for the machine learning. This included three primary steps: feature generation, feature selection, and data sampling.

A total of 36 initial features were generated: five occupant-behavior features (see Section 3.1), two building-size features (building floor area and number of floors), and 29 outdoor weather-condition features (extracted from the TMY3 weather data). The weekend and nonworking-weekday hours, during which the buildings are unoccupied and cooling energy consumption is zero, were removed from the dataset. One-hot encoding was used to convert the categorical variables to numerical.

Table 2
Envelope thermal properties of the buildings.

Surface	Materials (from outside to inside of the building)	U Value (W/m^2K)
Exterior wall	25.3 mm stucco + 203.3 mm heavyweight concrete block + 45.2 mm wall insulation + 12.7 mm gypsum	0.78
Interior wall	19 mm gypsum board + air gap + 19 mm gypsum board	0.14
Ground slab	101.6 mm concrete + carpet	0.10
Roof	9.5 mm roof membrane + 210.5 mm roof insulation + 1.5 mm metal decking	0.23
Window	3 mm theoretical glass	0.22

Table 3
Model locations and climate properties.

Location	Climate zone[a]	Climate description	CDDs[b]
Phoenix, AZ	1B	Very Hot - Dry	2532
Houston, TX	2A	Hot - Humid	1667
San Jose, CA	3C	Warm - Marine	398
New York, NY	4A	Mixed - Humid	672
Chicago, IL	5A	Cool - Humid	468

[a] According to the ASHRAE Standard 169–2020 [40].
[b] CDDs = cooling degree days.

The ordinal and continuous variables were normalized using their means and standard deviations to avoid the dominating effect of the features with high values. The resulting dataset included over 10 million hourly data instances.

For feature selection, first, features that are obviously irrelevant to energy consumption prediction (e.g., source of weather data) were removed, based on engineering judgement. Then, further feature selection was carried out, using neighborhood component analysis (NCA), to select the discriminating and non-redundant features. The NCA is a non-parametric and embedded feature selection method, which learns a feature weighting vector by minimizing an objective function that measures the average leave-one-out regression loss with a regularization term [41].

Subsequently, the data were sampled to reduce the computational cost of training the machine-learning models using such a large dataset and to evaluate the performance of the machine-learning algorithms with different sample sizes. The conditional Latin hypercube sampling (cLHS) method was used for the sampling, which is a stratified random procedure for sampling existing ancillary data [42]. Datasets with 1000, 2000, 5000, 10,000, 20,000, 50,000, 100,000, 200,000, 500,000, and 1, 000,000 data instances were sampled. Then, each dataset was randomly split into training, validation, and testing datasets with proportions of 65%, 10%, and 25%, respectively.

3.4. Machine-learning model development

A set of hourly cooling energy consumption prediction models were developed to test and compare different machine-learning algorithms in terms of prediction accuracy, computational efficiency (training time), and sensitivity to variations in sample sizes. Four machine-learning algorithms were tested: classification and regression tree (CART), ANN, EBT, and DNN. CART and ANN are among the most popular machine-learning algorithms in the field of building energy consumption prediction, whereas EBT and DNN are potentially superior but relatively less explored in this field. ANN is a nonlinear computational model, inspired by the human brain. A typical ANN includes three sequential layers: an input layer, a hidden layer, and an output layer. DNN is also a type of ANN, but it has more than one layer of hidden units between its input and output layers. CART uses a decision tree to map instances into predictions. In a CART model, each non-leaf node represents one feature, each branch of the tree represents a different value for a feature, and each leave node represents a class of prediction. Finally, EBT is an ensemble model that uses a bagging algorithm to ensemble a number of weak regression trees (e.g., CART). For the details of these algorithms the readers can refer to Ref. [9].

To assess the effect of ensembling on the prediction, the performances of the CART (single model) and the EBT (ensemble model) models were compared. The CART algorithm was trained with a minimum of four-leaf-node observations. The training of the EBT algorithm consisted of three main steps. First, 50 data subsets were generated by randomly sampling the training dataset with replacement. Second, a regression-tree-based weak learner was trained for each of the generated data subsets. Third, the weak learners were ensembled using the bagging algorithm, where the EBT's prediction is the average of the predictions made by the weak learners.

To understand the effect of the depth of the neural network models on the prediction, four different neural network models with different number of hidden layers were compared: an ANN algorithm, with 22 input neurons and 15 neurons in a single hidden layer; and three DNN algorithms, also with 22 input neurons, but with 15 neurons in two, three, and four hidden layers. The models were trained using the training dataset, the MATLAB's neural network training tool, and the statistical and machine-learning toolbox. The parameters of the machine algorithms were tuned through parameter grid search using the validation datasets, for each model to maximize the prediction performance. The final parameters are shown in Table 4.

3.5. Performance evaluation

Three performance metrics were used to evaluate the prediction performance of the models: coefficient of variation (CV), root mean square error (RMSE), and coefficient of determination (R^2). The trained models were used to predict the hourly cooling energy consumptions of the instances in the testing dataset. The predicted values were compared to the actual (simulated) values and the CV, RMSE, and R^2 were calculated, as per Eqs. (1)–(3). CV is a measure to assess the variability between the predicted and the actual energy consumptions. RMSE is the standard deviation of the residuals between the predicted and the actual energy consumptions. R^2 is a measure to assess how much of the variance in the actual energy consumption levels are explained by the model [43]. The lower the CV and RMSE and the higher the R^2, the more similar dispersions are between the predicted and the actual consumptions. CV was utilized as the primary performance metric, while RMSE and R^2 were only utilized as tie breakers when the CV did not show a significant difference between the models.

$$CV\ (\%) = \frac{\sqrt{\frac{\sum_{i=1}^{n}\left(y_{predict,i}-y_{data,i}\right)^2}{n}}}{\overline{y}_{data}} \times 100 \tag{1}$$

$$RMSE(kWh) = \sqrt{\frac{\sum_{i=1}^{n}\left(y_{predict,i}-y_{data,i}\right)^2}{n}} \tag{2}$$

$$R^2(\%) = \frac{\sum_{i=1}^{n}\left(y_{predict,i}-\overline{y}_{data}\right)^2}{\sum_{i=1}^{n}\left(y_{data,i}-\overline{y}_{data}\right)^2} \times 100 \tag{3}$$

where $y_{predict,i}$ is the predicted energy consumption at hour i, $y_{data,i}$ is the actual (simulated) energy consumption at hour i, n is the number of hours in the dataset, and $\overline{y}_{data}$ is the average energy consumption.

Table 4
Parameter tuning results.

Algorithm	Parameter	Value
CART	Minimum leaf size	4
EBT	Minimum leaf size	2
	Number of learners	50
	Fraction of training set to resample	1.0
ANN	Number of neurons in the hidden layer	15
	Training function	Bayesian regularization
	Activation function	Tan-Sigmoid
DNN	Number of hidden layers	2, 3, 4
	Number of neurons in each layer	15
	Training function	Bayesian regularization
	Activation function	Tan-sigmoid

4. Results and discussion

4.1. EnergyPlus simulation results

The EnergyPlus simulations generated a dataset with a range of occupant behaviors, building sizes, outdoor weather conditions, and resulting energy consumption values. Fig. 1 shows a sample of these simulation results. Fig. 2 aggregates the simulated hourly cooling energy consumption values to annual values for all models. As shown in Figs. 1 and 2, the range of energy consumption levels is wide. For example, the highest energy-consuming model used 3432.5 times more energy than the lowest-consuming model, which demonstrates the high impact of the variables considered in this study on building energy consumption. When only comparing same-size models, the highest consumer consumed 20.5 times more than the lowest consumer. This shows the combined impact of occupant behavior and outdoor weather conditions

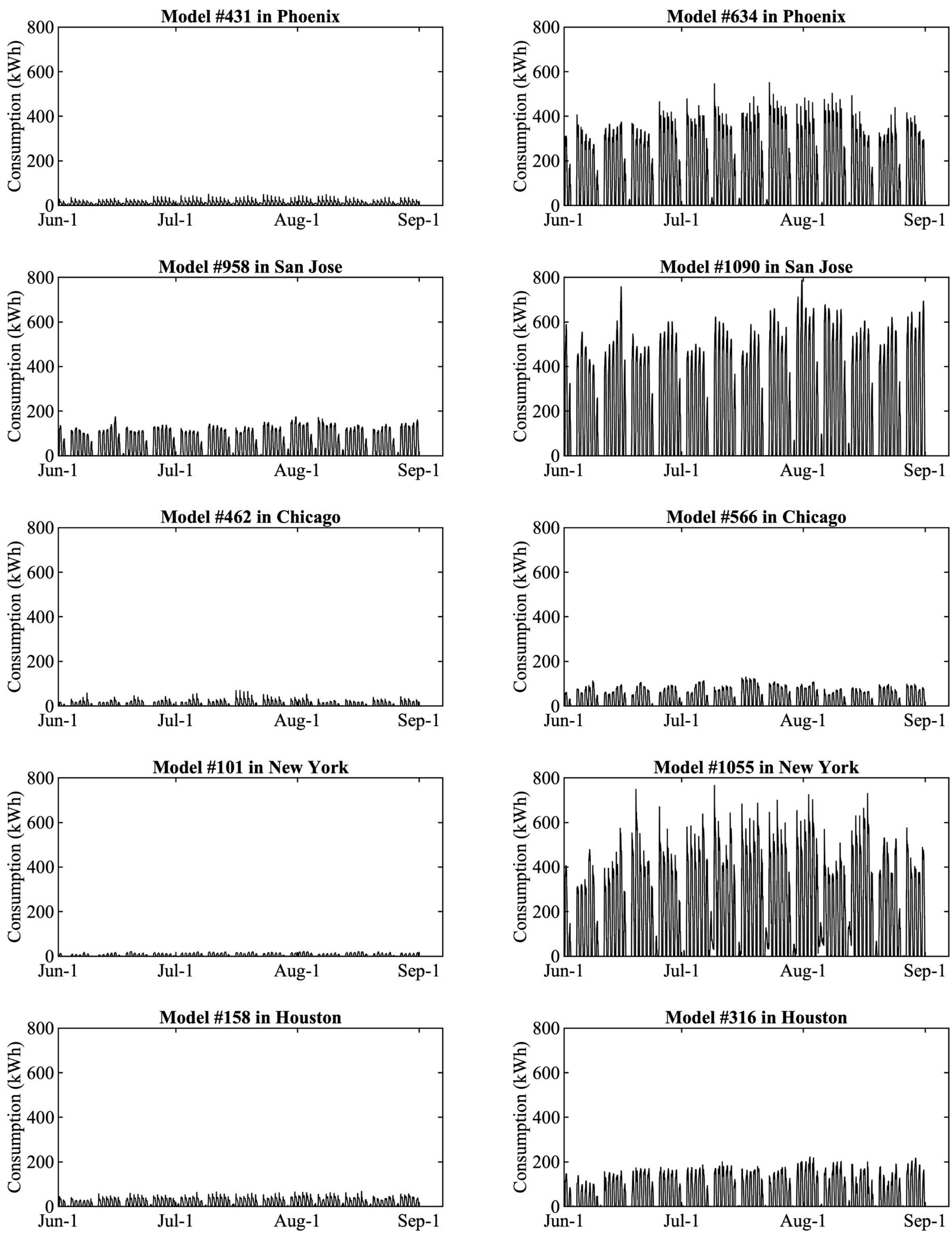

Fig. 1. Hourly cooling energy consumption levels of randomly selected models.

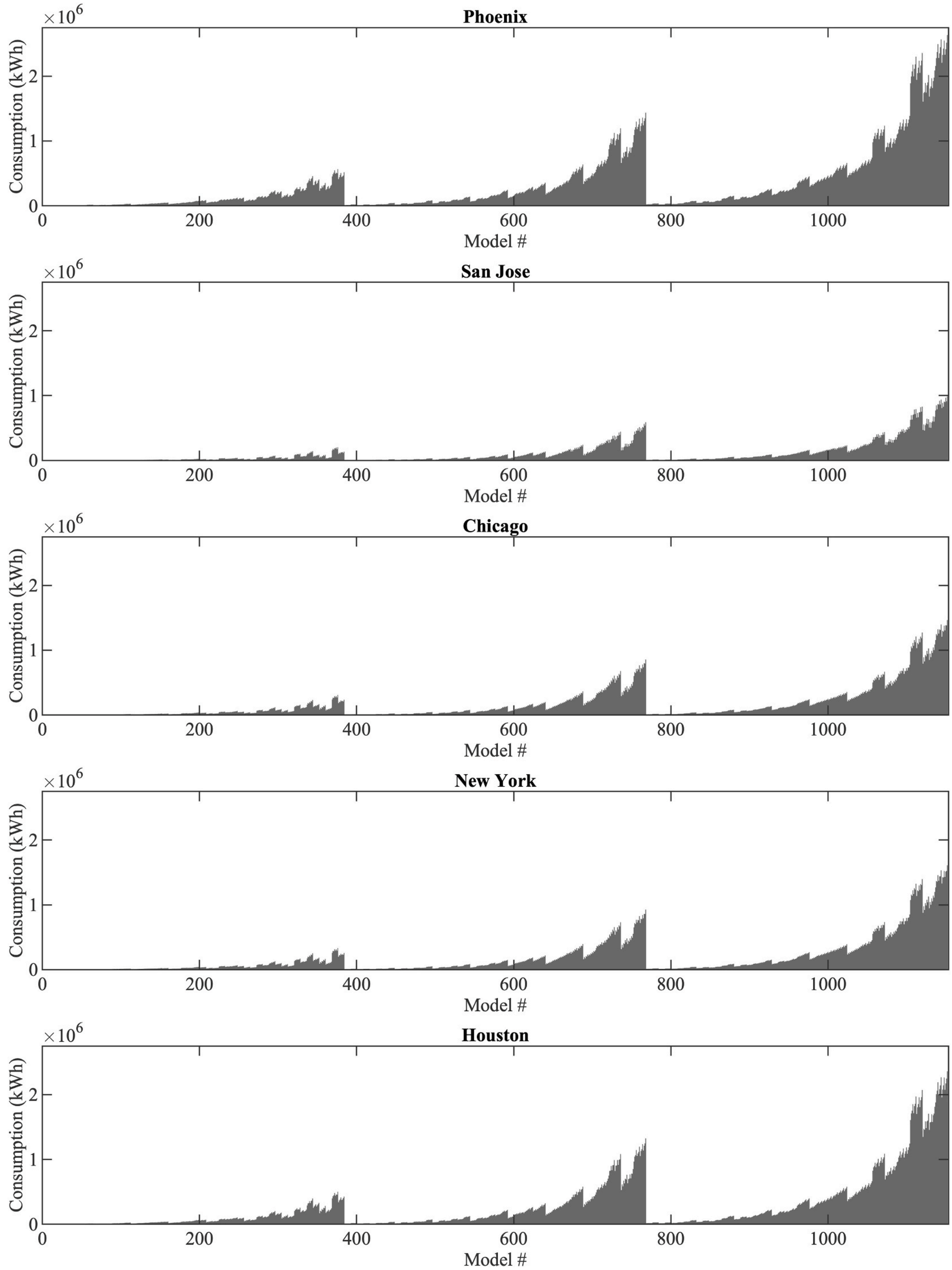

Fig. 2. Aggregated hourly cooling energy consumption levels for all models.

on energy consumption. Comparing models with the same building characteristics and in the same location, the highest energy consumer used 7.4 times more energy than the lowest consumer. This shows that occupant behavior, alone, has a major impact on building energy consumption.

4.2. Feature selection and data sampling

The feature selection and data sampling steps reduced the dimensionality and sample size of the dataset. The feature size was reduced from 36 to 12. The final, discriminating features that were used for the prediction included: (1) two building-property features: building size and number of floors, (2) eight outdoor weather-condition features: dry-bulb temperature, atmospheric pressure, extraterrestrial horizontal radiation, extraterrestrial direct normal radiation, horizontal infrared radiation intensity from sky, wind direction, wind speed, and precipitable water, and (3) two occupant-behavior features: cooling setpoint and window operation. Previous hours' values of these features were not utilized, because it would substantially increase the number of features, which would make the prediction models computationally expensive, more complex, and more prone to overfitting due to the increase in the model weights and/or parameters [2].

Looking at the energy simulation results, the final features had the highest impact on energy consumption. For example, a model consumed as much as 3.9 times more energy than another model with the same building characteristics, in the same location, and with the same occupant behavior except for only cooling setpoint. When comparing the models with differences in only window operation, the difference was as much as 2.7 times more. On the other hand, such high differences were not observed for the remaining, nondiscriminating features. For example, when comparing models with differences in only lighting power density, the maximum energy consumption difference was only 1.2 times more.

For data sampling, the sampled datasets (see Section 3.3) represented the characteristics of the original dataset. Fig. 3 shows the histogram of the cooling energy consumption of the original dataset. Fig. 4 shows the histograms of the cooling energy consumption of the sampled datasets. The sampled datasets preserve the characteristics of the original dataset, which are summarized in Table 5 and Fig. 3. For example, the frequency of energy consumption levels within the range of 0–250 kWh is 68.14% for the original dataset; while the same frequency is 67.20%, 68.80%, 68.84%, 68.15%, 67.59%, 68.06%, 68.11%, 68.19%, 68.16%, and 68.14% for the sampled datasets with 1000, 2000, 5000, 10,000, 20,000, 50,000, 100,000, 200,000, 500,000, and 1,000,000 hourly data instances, respectively.

4.3. Prediction performance

4.3.1. Prediction performance

Table 6 summarizes the prediction performance results of the four algorithms: CART, EBT, ANN, and DNN. When sufficient amounts of data were used for training, all four algorithms were able to achieve accurate predictions within reasonable training times. The ANN and DNN models may become computationally expensive to train in some sample sizes but can achieve very high prediction accuracies compared to the CART and EBT models. A number of findings can be drawn from the results of this study. First, the neural network models with the optimal number of hidden layers outperformed both the CART and EBT models in terms of prediction accuracy, for all 10 sample sizes. The highest prediction accuracy, 2.97%, was achieved by the DNN model with four hidden layers (trained using the 1,000,000 dataset in about 10 h). Second, the CART and EBT algorithms required more training data than the ANN and DNN algorithms to be considered calibrated. According to the ASHRAE Guideline 14 [44], an hourly prediction model is considered calibrated if its hourly CV values fall below 30%. For example, the ANN model required a minimum sample size of 1000,

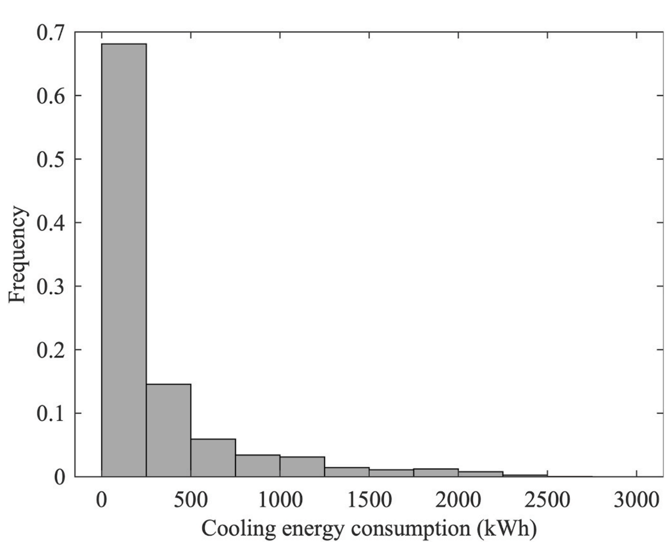

Fig. 3. Hourly cooling energy consumption levels of the original dataset.

compared to 5000 for the EBT model. Third, for all sample sizes, the training times of the CART and EBT algorithms were less than those for the ANN and DNN algorithms. For example, for a sample size of 100, 000, the DNN model with four hidden layers required 4122 s to train, while the CART model required only 1 s. Also, for a given training time period, the CART and EBT models achieved the highest prediction accuracies. For example, the EBT model could achieve 6.35% CV in 169 s (for a sample size of 1,000,000). But, in about the same time, the ANN model with a single hidden layer (for a sample size of 50,000) and the DNN model with two hidden layers (for a sample size of 10,000) could achieve 6.97% and 6.48%, respectively. Fourth, the DNN models were able to achieve a CV of less than 5% for sample sizes larger than 50,000, but the other algorithms were never able to achieve such low CV. However, the training time of the DNN to achieve such a high prediction accuracy was significantly higher than the other algorithms (e.g., 10 h vs. 7 s). The choice of the algorithm to use, therefore, depends on the application requirements (e.g., needed accuracy) and constraints (e.g., data availability).

4.3.2. Comparison of CART and EBT

In comparison to the CART models, the EBT models achieved higher accuracies but took longer times to train. These accuracy differences could have partially resulted from the characteristics of the original dataset. In general, the accuracy margin between the two types of models is more apparent in sparse datasets, because CART models suffer more from instability in sparse datasets [5]. In this study, the datasets were relatively diverse and sparse (because they represent different building sizes, weather conditions, and occupant behaviors), resulting in these significant accuracy differences. Such differences, however, may or may not be observed if other training datasets are used.

For all sample sizes, the CART models required less times to train than the EBT models. For example, for a sample size of 1,000,000, training the EBT model took about 25 times more than training the CART model. This is probably due to two reasons. First, EBT models require extra time due to data sampling. Second, for an EBT model, multiple models are trained on the same dataset, in comparison to only a single model for a CART model. Nevertheless, for all sample sizes, the training times of both types of models remained in acceptable ranges.

The most important advantage of the CART models is their transparent and explicit structures. The EBT models, however, are not as explicit as the CART models. But, in terms of prediction accuracy, the EBT models always outperformed the CART models. Since accuracy is highly important in many applications and contexts, EBT models can be preferred to CART models for building energy consumption prediction [5]. In general, the results show that the CART and EBT models are computationally inexpensive to train and can achieve good prediction accuracies. Thus, bagging should be one of the ensembling methods to consider when developing a building energy consumption prediction model.

4.3.3. Comparison of ANN and DNN

Shallower architectures outperformed deeper architectures for smaller datasets but fell below deeper architectures for larger datasets. For example, for sample sizes of 1000, 2000, and 5000, the typical ANN model with a single hidden layer outperformed the others in terms of prediction accuracy. For sample sizes of 10,000 and 20,000, the DNN model with two hidden layers outperformed. For all other larger datasets, the DNN models with four hidden layers outperformed as well. These results indicate that the increase in the number of hidden layers does not always guarantee an increase in the model performance. But, the increase in the number of hidden layers increased the model complexity and therefore caused longer training times. With larger datasets, on the other hand, deeper architectures always outperformed shallower architectures. This is consistent with the conclusions drawn by Fan et al. [2]: "The increase in the number of hidden layers leads to a dramatic increase in the number of model coefficients. To develop

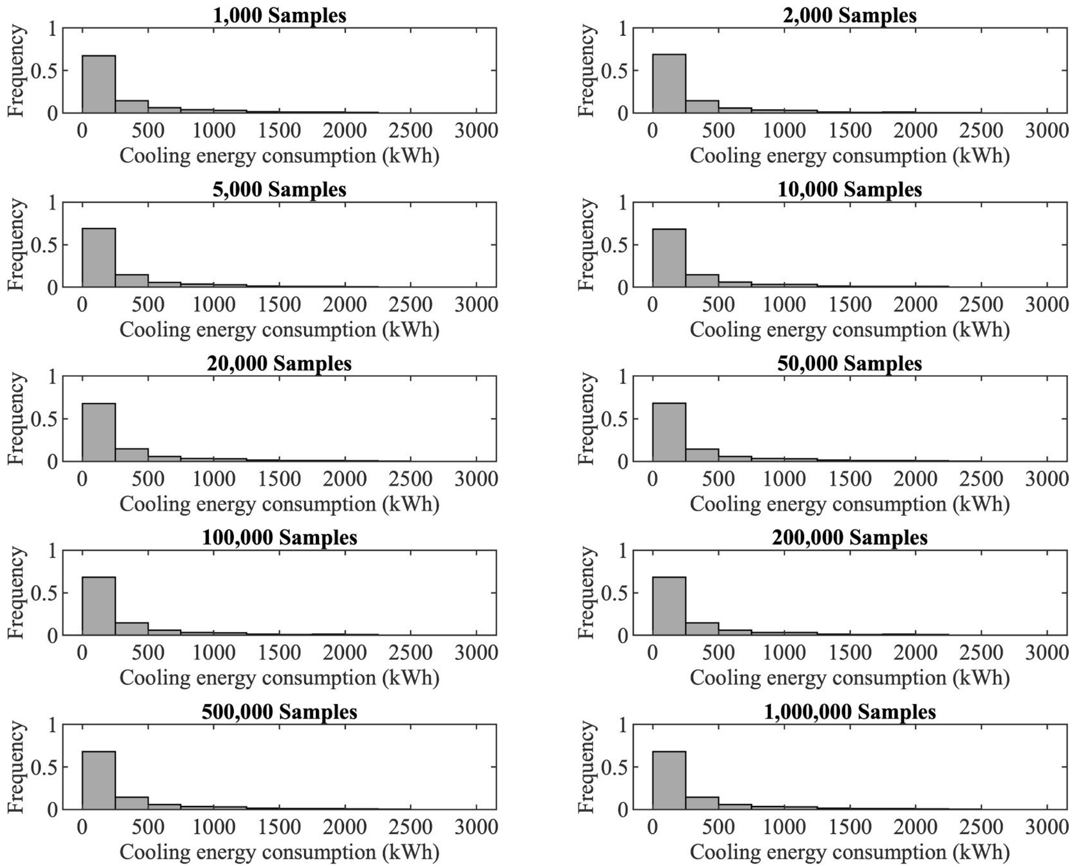

Fig. 4. Hourly cooling energy consumption levels of the sampled datasets.

Table 5
Statistics of the original dataset.

Feature	Min	Mean	Median	Max
Building size	2500	128,125	60,000	500,000
Number of floors	1	2	2	3
Cooling setpoint	22.8	24.0	24.0	25.2
Dry-bulb temperature	6.7	25.5	25.0	44.4
Atmospheric pressure	96,200.0	100,038.8	101,000.0	102,400.0
Extraterrestrial horizontal radiation	0	459.3	243.5	1311.0
Extraterrestrial direct normal radiation	0	781.6	1321.0	1342.0
Horizontal infrared radiation intensity from sky	273.0	395.5	396.0	531.0
Wind direction	0	183.2	190.0	360.0
Wind speed	0	3.6	3.6	16.0
Precipitable water	50.0	286.9	279.0	569.0

robust and reliable estimations of these model coefficients, a huge amount of data is needed".

In most sample sizes, the shallower architectures required much less time to train than the deeper architectures. For example, for a sample size of 1,000,000, training the DNN model with four hidden layers took about 14 times more than training the typical ANN model with a single hidden layer. One interesting result is the very low prediction accuracy and the very short training time of the DNN models with three and four hidden layers for the sample size of 1000. A possible explanation for this is overfitting. The use of larger number of hidden layers, more than the needed number to represent the complexity of the prediction function, leads to overfitting problems [45]. In addition, the training of the DNN model with four hidden layers using the sample size of 1,000,000 took about 10 h, which brings some practicality concerns despite the very high accuracy (2.97% CV) of the resulting model.

5. Limitations

Two main limitations of this study are acknowledged. First, the proposed prediction model learned from energy simulations, which could be limited in representing the complexity and stochastic nature of occupant behavior. Only a limited number of occupant behaviors were considered. In addition, the proxy behavior variables used for the energy simulations are by nature simplified, lacking the real-world complexity that may be encountered with actual occupant behavior. Nevertheless, the results of this study are important and help demonstrate the profound impact of occupant behavior on building energy consumption, as well as the feasibility and potential success of an occupant-behavior-sensitive energy consumption prediction approach. In their future work, the authors plan to further validate the proposed prediction model, and the behavior modeling approach, using real data collected from real buildings and real occupants. Second, in line with its intended scope, this study did not consider the impact of different building design decisions such as building thermal insulation. Future research efforts could further study the combined impact of both building design and occupant behavior on building energy consumption.

6. Conclusions, contributions, and future work

This paper presented a study on taking a machine-learning approach for predicting building energy consumption in an occupant-behavior-sensitive manner. In this approach, a model that learns from a large set of energy-use cases were modelled and simulated in EnergyPlus. The model was trained using 3-month hourly data for 5760 energy-use cases, representing different combinations of building characteristics, outdoor weather conditions, and occupant behaviors. In developing the model,

Table 6
Performance of the cooling energy consumption prediction models.

Sample size	Algorithm	CV	RMSE (kWh)	R^2	Training time (sec)
1000	ANN	5.55%	49.83	98.97%	7
	DNN {2}	8.38%	75.25	97.00%	67
	DNN {3}	168.73%	1515.69	−966.24%	1
	DNN {4}	220.72%	1982.64	−2051.82%	2
	CART	99.63%	894.96	74.72%	<1
	EBT	89.52%	804.11	79.59%	<1
2000	ANN	11.11%	30.13	99.49%	11
	DNN {2}	12.96%	35.13	99.18%	87
	DNN {3}	20.02%	54.27	97.91%	217
	DNN {4}	15.19%	41.19	98.83%	385
	CART	34.41%	93.28	93.90%	<1
	EBT	30.51%	82.72	95.20%	<1
5000	ANN	8.22%	22.95	99.72%	16
	DNN {2}	10.00%	27.93	99.59%	127
	DNN {3}	11.36%	31.72	99.38%	293
	DNN {4}	15.00%	41.90	99.14%	510
	CART	30.72%	85.81	96.39%	<1
	EBT	25.63%	71.60	97.49%	<1
10,000	ANN	7.65%	21.66	99.75%	15
	DNN {2}	6.48%	18.35	99.80%	177
	DNN {3}	8.46%	23.98	99.67%	390
	DNN {4}	9.88%	28.00	99.59%	739
	CART	22.04%	62.44	97.94%	<1
	EBT	18.14%	51.39	98.60%	1.55
20,000	ANN	7.04%	20.31	99.77%	43
	DNN {2}	5.50%	15.85	99.86%	267
	DNN {3}	5.93%	17.10	99.84%	591
	DNN {4}	7.40%	21.35	99.74%	997
	CART	17.36%	50.06	98.59%	<1
	EBT	13.77%	39.71	99.11%	2.1
50,000	ANN	6.97%	19.93	99.78%	149
	DNN {2}	4.88%	13.93	99.89%	548
	DNN {3}	4.43%	12.66	99.91%	1313
	DNN {4}	3.27%	9.33	99.95%	2172
	CART	14.59%	41.69	99.04%	<1
	EBT	10.82%	30.91	99.47%	6
100,000	ANN	7.48%	21.34	99.75%	323
	DNN {2}	4.65%	13.26	99.90%	1065
	DNN {3}	3.72%	10.62	99.94%	2496
	DNN {4}	3.21%	9.14	99.95%	4122
	CART	12.55%	35.80	99.27%	1
	EBT	9.00%	25.67	99.62%	11
200,000	ANN	7.20%	20.57	99.76%	481
	DNN {2}	4.77%	13.64	99.90%	1751
	DNN {3}	3.68%	10.51	99.94%	4503
	DNN {4}	3.19%	9.11	99.96%	7454
	CART	11.03%	31.50	99.46%	1.5
	EBT	7.94%	22.68	99.72%	22
500,000	ANN	7.40%	21.15	99.75%	1323
	DNN {2}	4.71%	13.45	99.90%	4800
	DNN {3}	3.88%	11.08	99.93%	11,920
	DNN {4}	3.54%	10.10	99.94%	17,534
	CART	9.27%	26.48	99.61%	3
	EBT	6.79%	19.40	99.79%	57
1,000,000	ANN	7.23%	20.67	99.77%	2559
	DNN {2}	4.88%	13.96	99.89%	9138
	DNN {3}	3.57%	10.22	99.94%	21,819
	DNN {4}	2.97%	8.50	99.96%	35,154
	CART	8.48%	24.27	99.67%	7
	EBT	6.35%	18.16	99.82%	169

DNN {x} x: number of hidden layers.

the CART, EBT, ANN, and DNN algorithms were tested and compared in terms of their prediction accuracy, computational efficiency, and sensitivity to variations in sample sizes. The simulation results showed that occupant behavior has a major impact on cooling energy consumption, with cooling setpoint and window operation being the most influential variables. The prediction results showed that all four algorithms were able to achieve accurate predictions when sufficient amounts of data were used. The ANN and DNN models were computationally expensive to train in some sample sizes, but were able to achieve very high prediction accuracies compared to the CART and EBT models. The neural network models with the optimal number of hidden layers outperformed both the CART and EBT models in terms of prediction accuracy, for all sample sizes. For example, the DNN model with four hidden layers, the most accurate model, achieved 2.97% CV. The CART and EBT algorithms required more training data than the ANN and DNN algorithms to be considered calibrated. For example, the ANN model required a minimum sample size of 1000, compared to 5000 for the EBT model. For all sample sizes, the training times of the CART and EBT algorithms were less than those for the ANN and DNN algorithms. For example, for a sample size of 100,000, the DNN model with four hidden layers required 4122 s to train, while the CART model required only 1 s. The DNN models were able to achieve a CV of less than 5% for sample sizes larger than 50,000, but the other algorithms were never able to achieve this level.

This work contributes to the body of knowledge on two main levels. First, this research offers a machine-learning approach for predicting building energy consumption in an occupant-behavior-sensitive manner. The proposed approach uses a set of proxy variables to represent and account for the behavior, in a simplified manner, in the energy simulations. The proposed approach could help better understand the impact of occupant behavior on building energy consumption, as well as identify opportunities for behavioral energy-saving measures and efficient building-operation strategies. Second, this study provides important insights to the field of machine learning-based energy consumption prediction. The results showed that the neural network model with the optimal number of hidden layers always outperformed both the CART and EBT models in terms of prediction accuracy. Shallower neural network models outperformed deeper neural network models in smaller datasets; whereas deeper models outperformed shallower models in larger datasets. Thus, the increase in the number of hidden layers in neural networks does not always guarantee an increase in accuracy. The EBT models always outperformed the CART models in terms of prediction accuracy. The accuracies of the four algorithms always increased as the sample size increased. The training times of the CART and EBT algorithms were less than the ANN and DNN algorithms. Thus, bagging should be one of the ensembling methods to consider when developing a building energy consumption prediction model. Given that there is no one-size-fits-all machine-learning algorithm, studying new algorithms in the context of building energy consumption prediction is critical.

In their future work, the authors plan to further improve the proposed behavior modeling approach and prediction model, with a focus on five main directions. First, the authors plan to study the combined impact of building characteristics, design decisions, and occupant behavior on building energy consumption. Second, the authors will test the proposed approach in real-life contexts – using real data collected from real buildings and real occupants – to validate the model and study how the modeling approach could be improved to better capture the complexity and stochastic nature of occupant behavior. Understanding and modeling occupant behavior and its impact, in a realistic manner, is crucial to realize the benefits of behavioral energy-efficiency efforts. Third, the authors plan to extend the proposed behavior-sensitive energy prediction approach to a smart grid context – moving from the building level to the smart grid level, as well as incorporating additional key features in the modeling such as occupant needs, preferences, and satisfaction. Occupants are key to efficient energy utilization in buildings. A good understanding of the energy use, comfort needs and preferences, and behavior of occupants – at both the individual and aggregate level – is essential to identifying successful incentive schemes and designing effective demand-response programs. Four, the authors plan to implement the proposed approach using online machine learning. Being able to update the prediction model using the real-time grid data would further improve the prediction accuracy and computational efficiency of the proposed approach. Fifth, the authors will establish an occupant-behavior-sensitive building energy management system (BEMS) framework to exploit the opportunities associated with behavioral energy-saving measures and efficient building-operation strategies using the state of the art control techniques such as model predictive control (MPC) and reinforcement learning (RL).

Credit Author statement

Kadir Amasyali: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. **Nora El-Gohary:** Conceptualization, Methodology, Validation, Resources, Data Curation, Writing – Review & Editing, Supervision, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] National Renewable Energy Lab. 2016 renewable energy data book. https://www.nrel.gov/docs/fy18osti/70231.pdf; 2017.
[2] Fan C, Xiao F, Zhao Y. A short-term building cooling load prediction method using deep learning algorithms. Appl Energy 2017;195:222–33. https://doi.org/10.1016/j.apenergy.2017.03.064.
[3] EIA. 2015 residential energy consumption Survey. https://www.eia.gov/consumption/residential/; 2015.
[4] Kc B, Ruth M. Estimation and projection of institutional building electricity consumption. Energy Build 2017;143:43–52. https://doi.org/10.1016/j.enbuild.2017.03.034.
[5] Wang Z, Wang Y, Srinivasan RS. A novel ensemble learning approach to support building energy use prediction. Energy Build 2018;159:109–22. https://doi.org/10.1016/j.enbuild.2017.10.085.
[6] Massana J, Pous C, Burgas L, Melendez J, Colomer J. Short-term load forecasting for non-residential buildings contrasting artificial occupancy attributes. Energy Build 2016;130:519–31. https://doi.org/10.1016/j.enbuild.2016.08.081.
[7] Chari A, Christodoulou S. Building energy performance prediction using neural networks. Energy Effic 2017;10:1315–27. https://doi.org/10.1007/s12053-017-9524-5.
[8] Wang Z, Srinivasan RS. A review of artificial intelligence based building energy prediction with a focus on ensemble prediction models. 2015 winter simul. Conf. IEEE; 2015. p. 3438–48. https://doi.org/10.1109/WSC.2015.7408504.
[9] Wei Y, Zhang X, Shi Y, Xia L, Pan S, Wu J, Han M, Zhao X. A review of data-driven approaches for prediction and classification of building energy consumption. Renew Sustain Energy Rev 2018;82:1027–47. https://doi.org/10.1016/j.rser.2017.09.108.
[10] Hong T, Sun H, Chen Y, Taylor-Lange SC, Yan D. An occupant behavior modeling tool for co-simulation. Energy Build 2016;117:272–81. https://doi.org/10.1016/j.enbuild.2015.10.033.
[11] Hong T, Taylor-Lange SC, D'Oca S, Yan D, Corgnati SP. Advances in research and applications of energy-related occupant behavior in buildings. Energy Build 2016;116:694–702. https://doi.org/10.1016/j.enbuild.2015.11.052.
[12] Clevenger CM, Haymaker JR, Jalili M. Demonstrating the impact of the occupant on building performance. J Comput Civ Eng 2014;28:99–102. https://doi.org/10.1061/(ASCE)CP.1943-5487.0000323.
[13] Ioannou A, Itard LCM. Energy performance and comfort in residential buildings: sensitivity for building parameters and occupancy. Energy Build 2015;92:216–33. https://doi.org/10.1016/j.enbuild.2015.01.055.
[14] Wang L, Greenberg S. Window operation and impacts on building energy consumption. Energy Build 2015;92:313–21. https://doi.org/10.1016/j.enbuild.2015.01.060.
[15] Sun K, Hong T. A simulation approach to estimate energy savings potential of occupant behavior measures. Energy Build 2017;136:43–62. https://doi.org/10.1016/j.enbuild.2016.12.010.
[16] Dong B, Cao C, Lee SE. Applying support vector machines to predict building energy consumption in tropical region. Energy Build 2005;37:545–53. https://doi.org/10.1016/j.enbuild.2004.09.009.
[17] Hong S-M, Paterson G, Mumovic D, Steadman P. Improved benchmarking comparability for energy consumption in schools. Build Res Inf 2014;42:47–61. https://doi.org/10.1080/09613218.2013.814746.
[18] Ascione F, Bianco N, De Stasio C, Mauro GM, Vanoli GP. Artificial neural networks to predict energy performance and retrofit scenarios for any member of a building category: a novel approach. Energy 2017;118:999–1017. https://doi.org/10.1016/j.energy.2016.10.126.
[19] Zhang Y, O'Neill Z, Dong B, Augenbroe G. Comparisons of inverse modeling approaches for predicting building energy performance. Build Environ 2015;86:177–90. https://doi.org/10.1016/j.buildenv.2014.12.023.
[20] Rastogi P, Khan ME, Andersen M. Gaussian-Process-Based emulators for building performance simulation. Proc. BS 2017;2017. https://doi.org/10.26868/25222708.2017.448.
[21] Paudel S, Elmtiri M, Kling WL, Le Corre O, Lacarrière B. Pseudo dynamic transitional modeling of building heating energy demand using artificial neural network. Energy Build 2014;70:81–93. https://doi.org/10.1016/j.enbuild.2013.11.051.
[22] Deb C, Eang LS, Yang J, Santamouris M. Forecasting diurnal cooling energy load for institutional buildings using Artificial Neural Networks. Energy Build 2016;121:284–97. https://doi.org/10.1016/j.enbuild.2015.12.050.
[23] Jain RK, Smith KM, Culligan PJ, Taylor JE. Forecasting energy consumption of multi-family residential buildings using support vector regression: investigating the impact of temporal and spatial monitoring granularity on performance accuracy. Appl Energy 2014;123:168–78. https://doi.org/10.1016/j.apenergy.2014.02.057.
[24] Platon R, Dehkordi VR, Martel J. Hourly prediction of a building's electricity consumption using case-based reasoning, artificial neural networks and principal component analysis. Energy Build 2015;92:10–8. https://doi.org/10.1016/j.enbuild.2015.01.047.
[25] Yu Z, Haghighat F, Fung BCM, Yoshino H. A decision tree method for building energy demand modeling. Energy Build 2010;42:1637–46. https://doi.org/10.1016/j.enbuild.2010.04.006.
[26] Amasyali K, El-Gohary NM. A review of data-driven building energy consumption prediction studies. Renew Sustain Energy Rev 2018;81:1192–205. https://doi.org/10.1016/j.rser.2017.04.095.
[27] Li K, Hu C, Liu G, Xue W. Building's electricity consumption prediction using optimized artificial neural networks and principal component analysis. Energy Build 2015;108:106–13. https://doi.org/10.1016/j.enbuild.2015.09.002.
[28] An N, Zhao W, Wang J, Shang D, Zhao E. Using multi-output feedforward neural network with empirical mode decomposition based signal filtering for electricity demand forecasting. Energy 2013;49:279–88. https://doi.org/10.1016/j.energy.2012.10.035.
[29] Ekici BB, Aksoy UT. Prediction of building energy consumption by using artificial neural networks. Adv Eng Software 2009;40:356–62. https://doi.org/10.1016/j.advengsoft.2008.05.003.
[30] Wang Zeyu, Wang Yueren, Zeng Ruochen, Srinivasan Ravi S, Ahrentzen Sherry. Random forest based hourly building energy prediction. Energy Build 2018;171(July):11–25. https://doi.org/10.1016/j.enbuild.2018.04.008.
[31] Tsanas A, Xifara A. Accurate quantitative estimation of energy performance of residential buildings using statistical machine learning tools. Energy Build 2012;49:560–7. https://doi.org/10.1016/j.enbuild.2012.03.003.
[32] Lahouar A, Ben Hadj Slama J. Day-ahead load forecast using random forest and expert input selection. Energy Convers Manag 2015;103:1040–51. https://doi.org/10.1016/j.enconman.2015.07.041.
[33] Jovanović RŽ, Sretenović AA, Živković BD. Ensemble of various neural networks for prediction of heating energy consumption. Energy Build 2015;94:189–99. https://doi.org/10.1016/j.enbuild.2015.02.052.
[34] Yousefi F, Gholipour Y, Yan W. A study of the impact of occupant behaviors on energy performance of building envelopes using occupants' data. Energy Build 2017;148:182–98. https://doi.org/10.1016/j.enbuild.2017.04.085.
[35] ASHRAE, ASHRAE Standard 189.1-2017, Standard for the design of high-performance green buildings. (2017).
[36] ASHRAE, ASHRAE Standard 55-2017, Thermal environmental conditions for human occupancy. (2017).
[37] Sun K, Hong T. A framework for quantifying the impact of occupant behavior on energy savings of energy conservation measures. Energy Build 2017;146:383–96. https://doi.org/10.1016/j.enbuild.2017.04.065.
[38] EIA. Cbecs 2012: building stock results. EIA; 2015. https://www.eia.gov/consumption/commercial/reports/2012/buildstock/.
[39] Hong T, Chen Y, Belafi Z, D'Oca S. Occupant behavior models: a critical review of implementation and representation approaches in building performance simulation programs. Build. Simul. 2018;11:1–14. https://doi.org/10.1007/s12273-017-0396-6.
[40] ASHRAE, ASHRAE standard 169-2020, climatic data for building design standards. (2020).
[41] Yang W, Wang K, Zuo W. Neighborhood component feature selection for high-dimensional data. J Comput 2012;7:162–8. https://doi.org/10.4304/jcp.7.1.161-168.
[42] Minasny B, McBratney AB. A conditioned Latin hypercube method for sampling in the presence of ancillary information. Comput Geosci 2006;32:1378–88. https://doi.org/10.1016/j.cageo.2005.12.009.
[43] Wang Z, Srinivasan RS, Shi J. Artificial intelligent models for improved prediction of residential space heating. J Energy Eng 2016;142:04016006. https://doi.org/10.1061/(ASCE)EY.1943-7897.0000342.
[44] ASHRAE, ASHRAE Guideline 14-2014, Measurement of energy, demand, and water savings. (2014).
[45] S. Karsoliya, Approximating number of hidden layer neurons in multiple hidden layer BPNN architecture, Int J Eng Trends Technol 3 (2012) 714–717.